Paving the way for increased e-health record use: Elaborating intentions of Gen-Z

This paper presents the determinants of personal e-health records adoption by the Gen-Z population and reveals barriers to use. Gen-Z members are one of the most prominent users of digital health services that have an influence on older generations' technology adoption but have often been overlooked in scholarly research. A survey of 1,000 Gen-Z university students based on a modified Unified Theory of Acceptance and Use of Technology model (UTAUT) was used to address this research gap. Privacy concerns, trust, and e-health literacy constructs helped improve the explanatory power of UTAUT in the e-health setting. Of the 479 valid questionnaires, 353 sets of responses from e-nabiz (an electronic health record system) users were analysed via structural equation modelling. The analysis revealed the vital role of social influence in paving the way for higher adoption among Gen-Z. Moreover, significant influences of performance expectancy, facilitating conditions, and e-health literacy on behavioural intentions were detected. Effort expectancy was found to be insignificant in impacting Gen-Z's intentions to adopt electronic health record systems. Moreover, privacy concerns acted as a barrier to adoption, yet the offsetting effect of users' trust in health systems was shown to be instrumental in overcoming such privacy-related barriers.

Keywords: e-health; health records; personal health records; Gen-Z; electronic health; preventive medicine

Introduction

Advances in information technology, and the digitization of health data, have enabled the development of tools that facilitate greater participation of patients in their own healthcare (Warraich et al., 2018). The wider adoption of enabling technologies and devices improves an individual's ability to access his/her health records conveniently via the Internet and provides efficiency, higher quality and accountability in health service delivery (Ammenwerth et al., 2019; Asaad Assiri, 2022; Shapiro & Kamal, 2021). Consequently, the future of health care is increasingly centred on citizens as they assume a more active role supported by governmental institutions that promote the use of electronic health records (EHR) and patient portals

(Ammenwerth et al., 2019; Baird et al., 2014; Portz et al., 2019). In fact, EHR systems originally emerged as collections of health information that are managed by healthcare providers and governmental institutions (Hertzum & Ellingsen, 2019). According to the WHO (2016) Global Survey on e-health, 59% of WHO member states have a national EHR system and 69% have legislation supporting the use of such systems. In Turkey, according to data for 2019, 11 million citizens use EHR (Aydın, 2019). In the last decade, EHRs have been integrated (i.e. tethered) to personal health records (PHR) or personally accessible electronic health record systems (PAEHRs), enabling citizens to easily access digital copies of their health provider-based information, such as diagnoses, treatments, medications, and laboratory test results.

Health care is an information-intensive industry and PAEHRs offer significant value to health systems by increasing the quality and safety of health care, cutting costs, improving efficiency, reducing medical errors, helping in diagnosis, and increasing compliance. Despite certain barriers from the perspective of clinicians (Windle et al., 2021), these outcomes can be achieved by consolidating and distributing patient data created by multiple healthcare providers and facilitating communication between patients and related organizations and professionals (Ammenwerth et al., 2019; Angst & Agarwal, 2006; Bhavnani et al., 2011; Dinev et al., 2016; Moll et al., 2018). Literature suggests that engaging patients in their health care via patient-centric initiatives such as providing easy access to personal health information improves patient attitudes, satisfaction, health care quality, and expected medical outcomes (Hearld et al., 2019; Heath & Porter, 2017; Shapiro & Kamal, 2021). Evidence also indicates that the adoption of EHR can be instrumental in reducing the racial gap in health outcomes (Koulayev & Simeonova, 2015). Thus, these tools may be instrumental in decreasing the burden on health systems worldwide that have been tested by the recent COVID-19 pandemic and in improving health outcomes.

Despite the benefits offered, certain factors limit the adoption of PAEHRs. Controversies and negative attitudes related to PAEHRs can result in rejection of the system (Dinev et al., 2016) and public resistance may limit the potential value of these technologies (Laugesen & Hassanein, 2017). For example, such technology-mediated services can alter the nature of face-to-face patient–provider relationships and patients may perceive such changes as uncertain and risky (Baird et al., 2014). Security concerns regarding personal health information, difficulty in interpreting health record information, and complex, hard-to-use systems can be counted among the common issues observed in the literature (Dontje et al., 2014; Portz et al., 2019). Older generations receive help using such e-health systems and technologies from their caregivers and younger family members, who can help overcome related barriers (Tieu et al., 2015). Considering wider adoption, younger generations, despite their digital literacy, may not feel the urge to use e-health systems. However, habits are hard to change at later ages, and the potential benefit of healthy behaviours at an early age is of considerable value to public health (Nayak et al., 2022; Schulenkorf et al., 2021). Furthermore, young people living with their families can help older family members in the use of new technology and systems, such as EHRs. Especially with the pandemic, it has become more common to work/study from home, search for health information electronically, and to use electronic health records more frequently (Demirhan & Eke, 2019). Consequently, Generation Z (Gen-Z) can have an indirect influence on the usage of e-health systems by older generations, who perceive these systems as difficult to use (Portz et al., 2019). However, the attitudes of the general public let alone younger generations towards EHRs are not well understood (Tulu et al., 2016) and extant research predominantly focuses on patients and older generations (Angst & Agarwal, 2009; Cimperman et al., 2016; Dontje et al., 2014; Honein-Abouhaidar et al., 2020; Portz et al., 2019; Wilson et al., 2021).

A limited number of studies suggest that age is an influential factor of perceptions and use, while lower age is associated with better attitudes towards and more frequent use of patient portals and EHRs (Baird et al., 2014; Tulu et al., 2016; Wen et al., 2010). Thus, Gen-Z emerges as a promising population to investigate in the context of e-health technology and health system adoption. Against this backdrop, it is imperative to address this research gap with the following research questions: 'What are the continued usage intentions of Gen Z with regards to PAEHR', 'What are the significant determinants of intentions to continued use of PAEHR?', 'Which factors emerge as barriers to PAEHR usage?' To address these questions, we have expanded UTAUT, a popular technology adoption model, to adapt it to an electronic health record system setting.

This article is structured as follows: The setting and literature on technology adoption and e-health records are reviewed in the first part, and then hypotheses are developed to construct the research model. The next section considers the methodology, which is followed by the study results. In the Discussion section, the findings are discussed in detail and theoretical contributions, in addition to practical and policy implications, are elaborated. Finally, the limitations of the study are presented, and the article is concluded in a separate Conclusion section.

Background

Setting: PAEHR in Turkey (e-pulse)

E-pulse (a.k.a. e-nabiz, https://enabiz.gov.tr), a PAEHR system managed by the Turkish Republic Ministry of Health, was chosen as the focal point of the study. E-pulse, launched in 2015, provides convenient access through the Internet to an individual's health information that is collected by health institutions (state and private) and health professionals (Turkish Republic Ministry of Health, 2019). Personal information on e-pulse such as weight and height can be modified by the individual. Health services information such as appointments, diagnosis, and treatment records, analysis results, radiological imaging results, and prescribed medicines are also provided (Aydın, 2019). Furthermore, e-pulse is integrated with the Turkish Organ and Tissue Donation System (European Commission, 2016). In e-pulse, the information can be viewed by physicians only if the individual has authorized access. Moreover, patients can evaluate the health services received and use navigation services to reach the nearest hospital or pharmacy via map app integration on mobile devices (Aydın, 2019). Table 1 summarizes the features of the system.

Table 1. E-pulse features

Feature	Function
Appointment Management	Patients can schedule or cancel healthcare service appointments.
Medical Record Center	Patients can view medical diagnosis details, immunization records, prescribed medicines, and care plans.
Lab and radiological Results	Patients can view test results.
Pharmacy and Hospital finder	Patients can look for nearby pharmacies and hospitals.
Navigation	Patients can get navigation help to reach target pharmacies or hospitals.
Personal information	Patients can enter their height and weight also can deny access to their health information record (this setting is on and off and not customizable).
Evaluation and feedback form	Patients can evaluate health services they have received using a satisfaction form.

EHR systems worldwide offer similar common features, yet certain value-added services such as teleconsultation or feedback mechanisms that can influence decision-making are provided only in specific countries. For example, Estonia, the first country in the world to fully implement an EHR system on a nationwide scale, has integrated all health care service providers, regardless of public or private ownership (Essén et al., 2018). Estonia's system also provides services such as booking appointments and screenings, e-prescription, teleconsultations, immunization passports, virtual health checks, and e-ambulance. In

Macedonia, the PAEHR system is integrated with e-health services and provides features such as registering for organ transplantation, shared decision-making on health policy, text notifications for appointment times, as well as a live dashboard showing requests, referrals, diagnoses, and prescriptions (WHO, 2016). In the UK, the EHR system also facilitates communication between patients and doctors (Bonomi, 2016). To establish the privacy and security of personal medical information in EHR systems, distinct features and modifiable settings are used. For example, in Denmark, patients can check who visited their profiles and can limit access to specific data and people by changing their settings. Similar to Turkey, in Italy, patient consent is required to process personal information (Bonomi, 2016). As can be seen from the aforementioned cases, EHR systems can offer various features to users that offer value to a multitude of stakeholders.

Theoretical framework: UTAUT and its use in healthcare

In studies on the adoption of new health care services and technologies, classical technology adoption models have been frequently adapted and used. Among these, the seminal work of Venkatesh et al. (2003), The Unified Theory of Acceptance and Use of Technology model (UTAUT), emerges as a pioneering study. UTAUT has integrated the major elements of widely used consumer behaviour and technology acceptance models, such as the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB), and the Innovation Diffusion Theory (IDT). This unified model was formulated using four major constructs and four moderators. UTAUT postulates that the intention to use a new information technology can be determined by three constructs: effort expectancy, performance expectancy, and social influence. Intention to use subsequently influences the actual behaviour of users, which is also influenced by enabling conditions, the fourth construct of the UTAUT model (Venkatesh et al., 2003).

UTAUT has since been used in a wide range of application areas of new technologies and systems, including healthcare (Cimperman et al., 2016; Kijsanayotin et al., 2009). However, considering that UTAUT was originally developed using technology adoption models that focus on workplace settings, various applications in health settings resulted in conflicting findings. UTAUT in its original form does not consider factors such as privacy concerns and risks related to the sharing of sensitive personal data or relevant literacy (i.e., health or digital) of users. This emphasizes the need to test the validity of the original model and expand it with context-specific constructs. Not surprisingly, in the last decade, researchers have benefitted from various modifications to UTAUT and have obtained deeper insights into e-health adoption (Dwivedi et al., 2016; Tavares & Oliveira, 2016; Yuan et al., 2015). Among these modifications, we see a certain focus on price value and hedonic motivation which led to UTAUT2 (Venkatesh et al., 2012). Also, a separate research stream focuses on privacy concerns related to e-health system use (e.g. Angst & Agarwal, 2009). Yet, given the current context of the present study, price value and hedonic motivation (e.g. entertainment, enjoyment) of UTAUT2 were considered to be insignificant since e-pulse is a free-to-use platform that does not aim to provide enjoyment. This phenomenon was observed in related studies that have adopted UTAUT2, yet failed to find any significant influence of these two constructs on intentions (Tavares & Oliveira, 2016). Entertaining features may help in motivating users to use business-related IT systems, the initial focus of UTAUT and its variants, yet these may be considered irrelevant or even insensitive in the health systems setting. Thus, we have adopted UTAUT and focused on three other relevant constructs namely users' privacy concerns, e-health literacy and trust. The first two were shown to be significant barriers to e-health adoption (Dontje et al., 2014; Hemsley et al., 2018), whiletrust in the health system and professionals is considered as a factor that can influence privacy concerns and continued usage intentions (Platt & Kardia, 2015).

Gen-Z and healthcare systems

Gen-Z, individuals born between 1995 and 2010, are also known as digital natives (Mat Zain et al., 2021). Compared to older generations who are traditionally reluctant to accept innovative health services (Coughlin et al., 2007), Gen-Z were provided access to the Internet and digital devices from an early age, so they are quick to adopt new technologies. They favour communication via technology (e.g. texting) rather than direct contact with people (Nicholas, 2020; Szymkowiak et al., 2021). Gen-Z members use the internet as an alternative source of information about health and medicines (Bachman, 2019; Papp-Zipernovszky et al., 2021). It was observed that health technology adoption and its determinants are influenced by the age of users (Andreassen et al., 2007). Younger generations more frequently use various forms of health technology, ranging from prescription refills, virtual doctor visits, online test results, and diet management, to tracking systems for fitness, health status, and medications (Rahman et al., 2021; Yousef et al., 2020).

In Turkey, which has a relatively young population compared to higher-income economies, the ratio of the population between the ages of 15-24 is 15.4% (Turkish Statistical Institute, 2021). Kilit and Eke (2019) demonstrated that the age range that researched the most health information online was 18-29 years old. This finding is in accordance with similar studies' findings in countries such as the UK (Harbour & Chowdhury, 2007). Given that individuals who use the Internet to search for health-related information and who use mobile health apps have higher odds of using PAEHRs (Yousef et al., 2020), Gen-Z is a prominent target of health system providers and policy makers. Furthermore, young people in Turkey generally live with their families for a long time before moving out (British Council, 2017) and help older family members learn to use new technology and systems. Especially with the pandemic, it has become more common to use EHRs and to search the Internet for health information (Demirhan & Eke, 2019).

Hypotheses development

Effort and performance expectancy

The effort expectancy construct of UTAUT, similar to the ease-of-use construct of TAM, is one of the essential determinants of technology acceptance. Effort expectancy was originally defined as “the degree of ease associated with the use of the system” by Venkatesh et al. (2003). In this study’s context, effort expectancy can be defined as ease of use associated with health IT systems(Kijsanayotin et al., 2009). Performance expectancy, on the other hand, was originally defined as: “the degree to which using a technology will provide benefits to consumers in carrying out certain activities” (Venkatesh et al., 2003). In other words, it can be defined as the degree to which an individual believes that using health IT will help him or her to attain gains in a healthcare system’s context (Kijsanayotin et al., 2009). In relevant studies on health system and technology adoption, performance expectancy and effort expectancy were found to be positively related to individuals’ intention to use a particular health system or technology (Albar & Hoque, 2019; Alloghani et al., 2015; Alsahafi et al., 2022; Cimperman et al., 2016; El-Wajeeh et al., 2014; Honein-Abouhaidar et al., 2020; Tavares & Oliveira, 2016; Wei et al., 2020; Zhao et al., 2018). Thus, these well-established factors, representing the functionality and benefits offered to users and how easy it is to use a system to utilize the benefits, were incorporated into the study with the following hypotheses:

H_1: Effort expectancy is positively related to users’ intention to continue using PAEHR.

H_2: Performance expectancy is positively related to users’ intention to continue using PAEHR.

Trust and privacy concerns

Personal health information, which is the most vital element of EHRs, is also among the most sensitive information an individual possesses. Considering that people tend to keep their personal medical information private and safe, privacy concerns have been found to influence the adoption of new health technologies and systems such as information exchanges and EHRs (Dinev et al., 2016; Mwachofi et al., 2016; Patel et al., 2012; Wilson et al., 2021). When using an EHR, for it to perform effectively, users have to disclose their data, thus placing those data in danger of being exposed. Consequently, reluctance to share personal information emerges as a major barrier to online healthcare services and systems adoption (Arfi et al., 2021; Baird et al., 2014; Bansal et al., 2010; Wilson et al., 2021) also to mobile health usage (Alaiad et al., 2019; Wei et al., 2020). Privacy concerns in this context can be defined as the perceived lack of confidentiality of personal information provided to an organization. Angst and Agarwal (2009), Wen et al. (2010) and Dinev et al. (2016) stated that an individual's concerns about information privacy affect attitudes toward the use of EHR and emerge as a usage barrier. Similar research and systematic reviews on e-health and m-health usage also highlighted 'privacy concerns' as a key determinant of behavioural intentions (Alloghani et al., 2015; Dontje et al., 2014; Mwachofi et al., 2016; Patel et al., 2012; Wei et al., 2020; Wilson et al., 2021; Zhang et al., 2019). Hence, we hypothesize that:

H_3: Privacy concerns are negatively related to users' intention to continue using PAEHR

Trust, in the EHR context, reflects an individual's perception about the protection of their personal health information by health care providers (Andrews et al., 2014). Jung and Loria (2010) stated that trust in the service provider can overcome barriers such as the risk of misunderstanding information, obtaining inaccurate information, or technical problems with security and privacy and recommended the inclusion of trust in future research. Andrews et al. (2014) revealed that higher perceived trust is positively related to attitudes towards PAEHRs.

Similarly, trust-related problems have emerged as a barrier to adoption among the older generations (Nymberg et al., 2019; Wilson et al., 2021) and the general population (Alloghani et al., 2015; El-Wajeeh et al., 2014) in various e-health settings. In addition to its impact on intentions, there is evidence of trust being influential in decreasing the privacy risk related to e-health usage (Arfi et al., 2021; Dinev et al., 2016; Platt & Kardia, 2015). From a health systems management perspective, to leverage EHRs properly, the collected data should be accurate and rich. Consequently, it is critical to understand the influence of privacy issues and of trust in healthcare institutionsamong new generations (i.e. Gen-Z) on disclosing personal health information and using EHRs. Therefore, we hypothesize the following:

H_4: Trust is negatively related to users' privacy concerns.

H_5: Trust is positively related to users' intention to continue using PAEHR.

Social influence, facilitating conditions, and e-health literacy

Social influence is a direct determinant of behavioural intentions according to UTAUT and is defined as the degree to which an individual considers that significant others believe he or she should use a new technology or system (Cimperman et al., 2016; Venkatesh et al., 2003). Social influence was found to be instrumental in changing individuals' thoughts, attitudes, or behaviours resulting from interaction with other individuals/groups (Albar & Hoque, 2019; Alsahafi et al., 2022; Arfi et al., 2021; El-Wajeeh et al., 2014). It has also been observed that patients' adoption of healthcare technology is influenced by their caregivers or younger family members, thus positive social influence increases users' intention to use such novel systems (El-Wajeeh et al., 2014; Honein-Abouhaidar et al., 2020). Further evidence from a meta-analysis of 35 studies highlighted the role of social influence in the use of mobile health services (Zhao et al., 2018). Also, Gen-Z's particular interest in the views of others, and their propensity to get influenced by their peer groups and other influencers in the healthcare context, was confirmed by novel studies on wearables and vaccinations (Cheung et al., 2020; Jose, 2021). Considering UTAUT and these findings, we hypothesize:

H_6: Social influence is positively related to users' intention to continue using PAEHR.

The facilitating conditions construct in UTAUT is defined as "the degree to which an individual believes that a technical and organizational infrastructure exists to support the use of the system" (Cimperman et al., 2016; Venkatesh et al., 2003). Cimperman et al. (2016) studied older users' telehealth service acceptance and Cajita et al. (2018) studied mHealth adoption among older patients and found facilitating conditions to be a determinant of behavioural intentions. Similarly, Kijsanayotin et al. (2009) specified a significant positive relationship between facilitating conditions and intentions in the healthcare domain, and Wilson et al. (2021) highlighted the significance of facilitating conditions on e-health use among older adults in their systematic literature review. Consequently, we hypothesize:

H_7: Facilitating conditions are positively related to users' intention to continue using PAEHR.

A relevant construct similar in nature to facilitating conditions but that covers the relevant digital skills in a more detailed manner is electronic health literacy (EHL). Internet technologies provide access to health information; however, an abundance of information of varying quality (i.e. misleading or false information) poses certain risks. Being health literate in a digital setting requires skills such as health literacy, information literacy, media literacy, and computer literacy (Schulenkorf et al., 2021). Moreover, e-health services targeting the general populace require the skill to effectively find, evaluate, and apply what is learned online to a health problem. This skill, termed as e-health literacy, necessitates that individuals can work with a technology, critically think about issues of media and science, and explore a wide range of information tools and sources to acquire the information necessary to make decisions (Norman & Skinner, 2006). Relatedly, low computer literacy and health literacy were stated as key factors influencing health information technology adoption (Hemsley et al., 2018; Showell

& Turner, 2013; Uslu & İpek, 2022; Wilson et al., 2021; Witten & Humphry, 2018). Hence, we hypothesize:

H_8: E-health literacy is positively related to users' intention to continue using PAEHR.

EHR use, gender and system experience

In UTAUT, gender, age and experience have been considered significant moderators that influence the relationships between constructs. There is empirical evidence of such moderation postulated in UTAUT within the e-health adoption literature (Nunes et al., 2019; Tavares & Oliveira, 2016). Consequently, we have tested for the significance of gender and experience as moderators, yet excluded the age of the respondents as they were quite close to each other (18-22) due to the sample characteristics. Hence the following was hypothesized:

H_9: Gender and experience will moderate the relationship between PAEHR continued usage intentions and its determinants.

The research model developed upon UTAUT and inspired by the existing knowledge on e-health system use and EHR adoption is visualized in Figure 1.

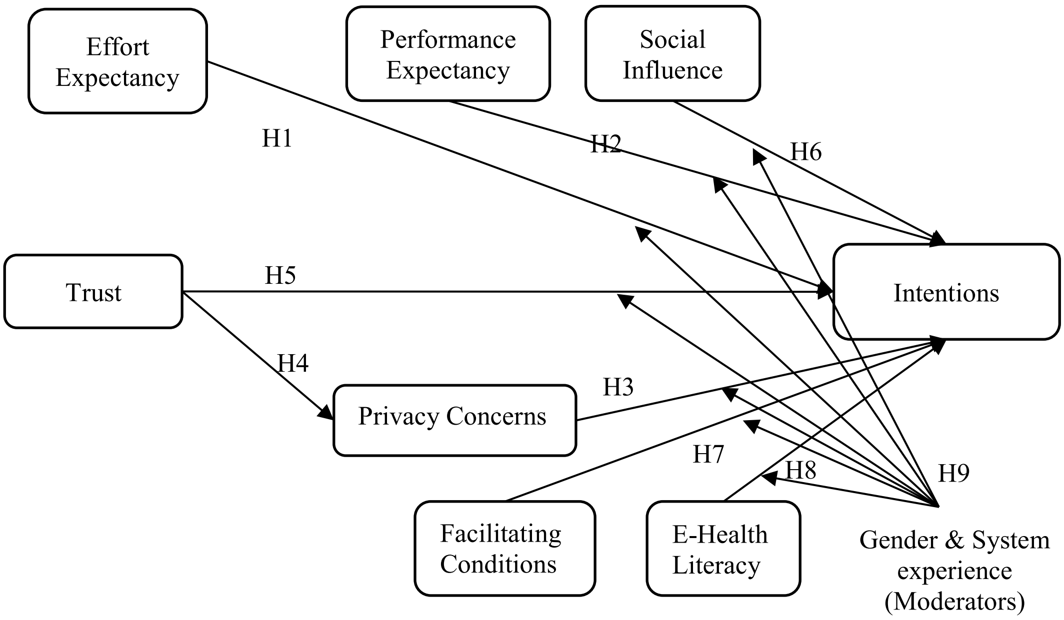


Figure 1. Proposed model

Method

A cross-sectional survey design was employed to examine the hypotheses. Data were collected via a questionnaire form completed by the target population, Gen-Z members with PAEHR (i.e. e-pulse) experience. We have considered people born between 1995 and 2010 as Gen-Z members in line with McKinsey's definition (Francis & Hoefel, 2018). Considering that novel technology users are early adopters and have high education levels (Wen et al., 2010), and also taking into account that students use digital resources (e.g. the Internet) and relevant online services more frequently than the general public (Harbour & Chowdhury, 2007), a student sample was deemed suitable. Furthermore, as the objective was not to provide point and interval estimates of population parameters, a student sample is considered adequate for this study (Calder et al., 1981). Purposive sampling was used in reaching the target population by implementing the study in four universities (two private and two stateowned) in Turkey. A total of 1,000 surveys were distributed and of the 569 forms collected (56.9% response rate), 90 were left out of the study due to partially filled forms. It was clearly indicated that the responses will be anonymized, no personally descriptive information would be collected, and only individuals with knowledge of the e-pulse PAEHR system should participate in the survey study. The respondents were asked to indicate whether they are currently using PAEHR at the beginning of the survey and nonusers are forwarded to a section where they can provide their main reason for not using the system. The characteristics of the respondents are provided in Table 2.

Table 2. Sample characteristics

Variable	Value	Frequency (n)	Percent (%)	Valid Percent (%)
Users	Total	353	73.7%	73.7%
Non-users	Left out of SEM analysis	126	26.3%	26.3%
Characteristics of Respondents who identified themselves as 'Users'				
Gender	Female	244	69.1%	72.6%
	Male	92	26.1%	27.4%
	NA/Missing	17	4.8%	-
Age	18.0	42	1.2%	12.5%
	19.0	111	31.4%	33.0%
	20.0	100	28.3%	29.8%
	21.0	34	9.6%	10.1%
	22.0+	49	13.9%	14.6%
	NA/Missing	17	4.8%	-
University	State	150	42.5%	42.5%
	Private	183	57.5%	57.5%
Income (USD Equivalent)	$ 0-350	51	14.4%	16.0%
	$ 351-700	98	27.8%	30.8%
	$ 701-1,050	84	23.8%	26.4%
	$ 1,051-1,400	43	12.2%	13.5%
	$ 1,401-1,750	18	5.1%	5.7%
	$ 1,751+	24	6.8%	7.5%
	NA/Missing	35	9.9%	-
PAEHR Experience	Low (Use rarely)	202	57.2%	58.5%
	High (Use frequently)	143	40.5%	41.5%
	NA/Missing	8	2.3%	-
Grand Total		479	100%	100%

The constructs in the model were operationalized using the extant literature on e-health adoption. Given that actual use behaviour is unknown, respondents' intention to continue using PAEHR, a proxy for adoption, was used as the focal construct. The items that were adopted from influential studies to measure and assess the constructs are provided in Appendix-A. All measures are reflective and measured using a 7-point Likert scale (1: Strongly Disagree to 7: Strongly Agree). Non-users were posed a multiple-choice question in order to determine their main reasons for not using PAEHR. The options consisted of closed-end items that highlight the main barriers to use (i.e. features, needs, complexity, privacy risks, literacy, awareness) along with an 'other' category to enable text input to collect further feedback. The responses obtained are summarized in Table 3.

A pre-test was conducted before finalizing the measurement instrument, starting with a review by four scholars to assess the comprehensibility and formatting of the draft form. After implementing the suggested revisions in the wording and introductory explanations, twelve university students pretested the modified questionnaire to provide feedback on the design, wording, question formats, and length of the questionnaire. Following minor changes, the measurement instrument was finalized.

Data analysis

The data was coded, recoded, and initially analysed in SPSS 21. Considering the high number of paths to be tested, the relatively limited sample size, and possible deviations from normality we have chosen PLS-SEM, to analyse the data, given that it's a method which can handle complex models and has lenient assumptions regarding data distribution. SmartPLS 3.2 software was used to carry out PLS-SEM analysis on the valid responses collected from 353 users. After an initial run, one item from the e-health literacy construct with low loading (<0.70) was excluded from further analysis.

Results

The reasons that nonuser respondents indicated for not using the PAEHR are provided in Table 3. A lack of a need to use the system is highlighted as the main reason for not using the system (36%) followed by lack of perceived benefits (18%) and privacy concerns (16%).

Table 3. Reasons for not using PAEHR

Reasons for not using PAEHR (one answer per respondent)	**n**	**%**
Did not feel any need to use the system	45	36%
Don't believe the system is beneficial	23	18%
Data privacy and confidentiality concerns	20	16%
Hard to use / complicated	15	12%
Don't know enough about the system	13	10%
Other reason	10	8%
Total	126	100%

The goodness-of-fit was assessed using the standardized root mean square residual (SRMR) and root mean square residual covariance (RMS_{theta}), the coefficient of determination (R^2) of latent variables, the statistical significance levels of the paths and Stone-Geisser's Q^2 value, as proposed in the literature (Hair et al., 2017). SRMR value of 0.047 and RMS_{theta} value of 0.120 indicated an acceptable fit (Henseler et al., 2016). R^2 for intentions was calculated as 0.292, indicating that the model accounted for a significant amount of variance (Hair et al., 2017). Finally, the Stone-Geisser Q coefficient (Q^2) was used to assess the predictive validity of the model through blindfolding. The Q^2 value for intentions was calculated as 0.247, indicating good predictive validity of the model (Cohen, 1988). Given these findings, the model was considered to fit the data properly and has good predictive power.

Subsequently, the validity and reliability of the scales were assessed, the results of which are provided in Table 4. First, each variable's correlation with other variables was compared to the square root of the average variance extracted (AVE) values to assess the discriminant validity of the model (Fornell & Larcker, 1981). All AVE square root values were lower than the correlations with other constructs. Furthermore, the inter-item correlations established that correlations between the items measuring different latent variables were below the 0.60 threshold. This supported the discriminant validity of the model, also implying that multicollinearity is not an issue in the present study (Hair et al., 2017). The convergent validity of the model was assessed by Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE) values. All CA and CR values were at acceptable levels (>0.7). Similarly, all AVE figures were higher than the 0.5 threshold. The variance inflation factor values, which were all lower than 10, further indicated a lack of multicollinearity in the model. Depending on the validity and reliability analyses carried out, the research model satisfied the acceptable standards put forward in the relevant literature.

Table 4. Reliability and validity

	CA	rho_A	CR	AVE	EHL	EFE	FAC	INT	PRI	SOC	TRU	PRF
EHL	0.933	0.935	0.946	0.714	**0.845**	0.462	0.495	0.355	0.088	0.320	0.336	0.376
EFE	0.915	0.917	0.940	0.797	0.429	**0.893**	0.769	0.404	0.061	0.406	0.550	0.722
FAC	0.820	0.829	0.881	0.650	0.437	0.754	**0.806**	0.460	0.070	0.413	0.574	0.792
INT	0.915	0.916	0.946	0.855	0.330	0.372	0.402	**0.925**	0.181	0.432	0.310	0.458
PRI	0.953	0.960	0.964	0.844	-0.087	-0.048	-0.055	-0.171	**0.918**	0.031	0.233	0.080
SOC	0.892	0.898	0.933	0.822	0.290	0.366	0.357	0.393	0.011	**0.907**	0.392	0.443
TRU	0.897	0.907	0.923	0.707	0.308	0.491	0.488	0.284	-0.223	0.349	**0.841**	0.670
PRF	0.897	0.901	0.936	0.829	0.346	0.655	0.678	0.417	-0.071	0.398	0.603	**0.911**

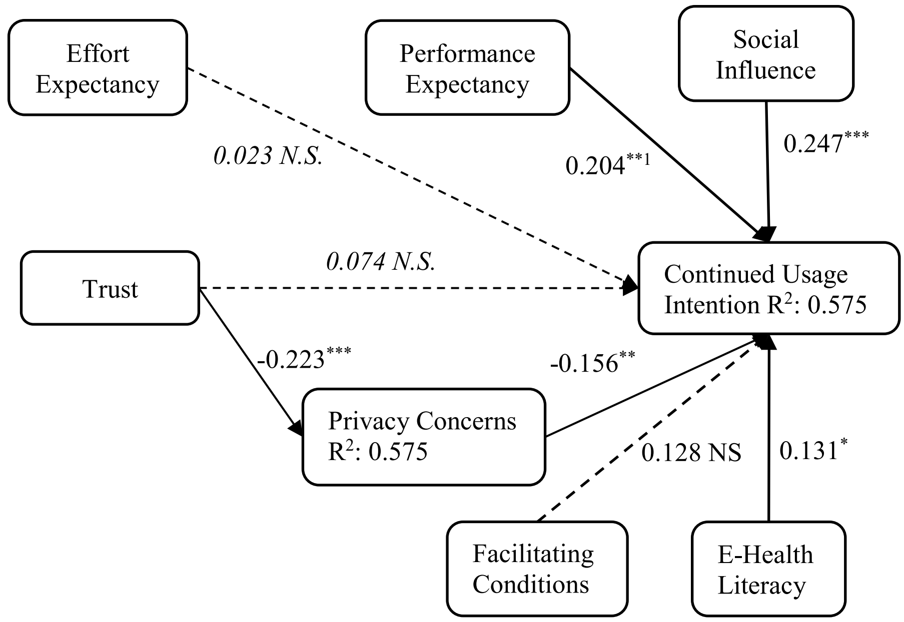
Notes: Square-roots of AVE are provided on the diagonal, correlations below the diagonal and HTMT over the diagonal. EHL:E-health literacy, EFE: Effort expectation, FAC: Facilitating conditions, INT: Continued Usage Intentions, PRI: Privacy concerns, TRU: Trust, SOC: Social influence, PRF: Performance expectancy

The concern for common method variance was addressed in the design and administration of the study. First, the anonymity of respondents was assured and plain language with minimal technical terms was preferred. Additionally, it was emphasized that there are no correct or incorrect answers. During the analysis stage, the severity of the common method variance was tested using Harman's single factor test, which was calculated as 33%. Thus, the variance explained by the one-factor solution is lower than the 50% threshold, specifying that common method variance is not a significant issue in the study (Podsakoff et al., 2003). The descriptive statistics of the constructs are provided in Table 5.

Table 5. Descriptive statistics

Constructs (N=353; Range 1-7)	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**
Trust (TRU)	5.193	1.250	-1.210	1.378
Performance Expectancy (PRF)	5.745	1.122	-1.699	3.900
Effort Expectancy (EFE)	5.692	1.092	-1.612	3.300
Facilitating Conditions (FAC)	5.721	1.122	-1.710	3.863
Social Influence (SOC)	4.704	1.346	-0.610	0.353
E-Health Literacy (EHL)	5.165	1.235	-0.960	1.070
Privacy Concerns (PRI)	4.156	1.613	-0.160	-0.880
Continued Usage Intentions (INT)	5.046	1.333	-0.505	-0.061

The respondents on average have positive intentions to continue using PAEHRs (mean: 5.05/7). Privacy concerns, with an average score of 4.16 on a 7-point Likert scale, and a relatively high standard deviation (1.61), indicated heterogeneity in the sample regarding concerns about the privacy of personal information. Similar findings in the literature also support this phenomenon of mixed dispositions (Dontje et al., 2014). Skewness and kurtosis figures in Table 4 also demonstrate that there are deviations from normality. The path analysis results are provided in Figure 2 and Table 6.



*Significance levels: *<0.05; **<0.01; ***<0.001; dashed lines - NS: not significant*
[1]: significant moderation by system experience

Figure 2. Path analysis results

Table 6. Path analysis & hypothesis testing

Paths	Mean	S.D.	T-Stat.	P Value	Hypothesis
Effort Expectancy -> Intentions	0.023	0.066	0.356	0.724	H1: Reject
Performance Expectations -> Intentions	0.204	0.075	2.746	0.006	**H2: Accept****
Privacy -> Intentions	-0.156	0.046	3.385	0.001	**H3: Accept*****
Trust -> Privacy Concerns	-0.223	0.054	4.148	0.000	**H4: Accept*****
Trust -> Intentions	0.074	0.071	1.057	0.291	H5: Reject
Social Influence -> Intentions	0.247	0.056	4.426	0.000	**H6: Accept*****
Facilitating Conditions -> Intentions	0.128	0.076	1.692	0.084	H7: Reject
EHealth Literacy -> Intentions	0.131	0.064	2.069	0.039	**H8: Accept***

*Significance levels: * <0.05; **<0.01; ***<0.001*

Following the path analysis, the role of gender and system experience as moderators were analysed. Three different tests, namely permutation (PLS-MultiGroupAnalysis), parametric and nonparametric (Welch-Satterthwait test), were used in assessing moderation as suggested in the relevant PLS-SEM literature (Hair et al., 2017; Sarstedt et al., 2011). All three tests indicated that there were no significant differences between males and females regarding the tested relationships. On the other hand, the relationship between performance expectancy and intentions was found to be significantly higher for the high-experienced subsample compared to the low-experienced subsample. No other statistically significant differences were detected between the low and high-experience subsamples, thus H_9 was partly accepted. Details of the analysis results are provided in Table 7.

Table 7. Testing the Moderating role of Gender and Experience

Gender Groups: Male (n: 92) - Female (n: 244)		PLS-MGA		Parametric Test		Welch-Satterthwait Test	
Paths	Coefficient difference	p value original	p value	t value	p value	t value	p value
E-Health Literacy -> Intentions	0.029	0.401	0.802	0.218	0.828	0.238	0.812
Effort Expectancy -> Intentions	0.112	0.219	0.438	0.773	0.440	0.780	0.437
Facilitating Conditions -> Intentions	-0.199	0.894	0.212	1.206	0.229	1.238	0.218
Performance Expectancy -> Intentions	0.092	0.304	0.607	0.535	0.593	0.519	0.605
Privacy -> Intentions	-0.156	0.920	0.161	1.493	0.136	1.393	0.167
Social Influence -> Intentions	-0.168	0.934	0.131	1.360	0.175	1.516	0.132
Trust -> Intentions	0.077	0.296	0.592	0.510	0.610	0.537	0.592
Trust -> Privacy	0.024	0.407	0.814	0.186	0.852	0.195	0.845
Experience Groups: Low (n_{low}:202) - High (n_{high}:143)							
E-Health Literacy -> Intentions	-0.015	0.554	0.892	0.121	0.904	0.125	0.901
Effort Expectancy -> Intentions	0.145	0.161	0.322	1.029	0.304	0.987	0.325
Facilitating Conditions -> Intentions	-0.116	0.776	0.448	0.769	0.442	0.748	0.456
Performance Expectancy -> Intentions	**0.377**	**0.007**	**0.014**	**2.514**	**0.012**	**2.447**	**0.016**
Privacy -> Intentions	0.001	0.497	0.993	0.013	0.989	0.013	0.989
Social Influence -> Intentions	0.035	0.367	0.734	0.325	0.745	0.328	0.744
Trust -> Intentions	-0.263	0.966	0.068	1.827	0.069	1.841	0.068
Trust -> Privacy	-0.022	0.588	0.824	0.211	0.833	0.213	0.831

Discussion

This study investigated the factors that influence PAEHR adoption and has validated all hypothesized relationships excluding H_1 (Effort expectancy -> Intentions), H_5 (Trust -> Intentions) and H_7 (Facilitating Conditions -> Intentions). Our findings and related literature findings are summarized in Table 8 to provide an easy-to-digest comparison grouped by generations. These findings are discussed in more detail in this section.

Table 8. Comparative analysis of findings

Determinants of Intention to Use	Target Population	Study's Findings vs. Literature	
		Significant	Not Significant
Effort Expectancy	General	(Alloghani et al., 2015; Alsahafi et al., 2022; Arfi et al., 2021; El-Wajeeh et al., 2014; Kijsanayotin et al., 2009)	(Lee et al., 2020)
	Older	(Cimperman et al., 2016; Honein-Abouhaidar et al., 2020)	
	Younger	(Tavares & Oliveira, 2016)	**EE is not positively related to intentions.** (Almazroi et al., 2022)
Performance Expectancy	General	(Alloghani et al., 2015; Alsahafi et al., 2022; El-Wajeeh et al., 2014; Kijsanayotin et al., 2009; Lee et al., 2020; Wei et al., 2020)	(Arfi et al., 2021)
	Older	(Cimperman et al., 2016; Honein-Abouhaidar et al., 2020)	
	Younger	**PE is positively related to intentions.** (Almazroi et al., 2022; Cheung et al., 2020; Suwannapusit, 2021; Tavares & Oliveira, 2016; Yuan et al., 2015)	
Facilitating conditions NS	General	(Arfi et al., 2021; Lee et al., 2020)	
	Older	(Cajita et al., 2018; Cimperman et al., 2016; Zibrik et al., 2015)	
	Younger		**Facilitating conditions is not positively related to intentions.** (Keen & Roberts, 2017; Suwannapusit, 2021; Tavares & Oliveira, 2016; Yuan et al., 2015)
Social Influence	General	(Albar & Hoque, 2019; Alsahafi et al., 2022; Arfi et al., 2021; El-Wajeeh et al., 2014; Kijsanayotin et al., 2009)	(Lee et al., 2020)
	Older	(Zibrik et al., 2015)	(Cimperman et al., 2016)
	Younger	**SI positively related to intentions and has the strongest influence on intentions**. (Keen & Roberts, 2017)	(Suwannapusit, 2021; Tavares & Oliveira, 2016; Yuan et al., 2015)
Trust	General	(Alloghani et al., 2015; El-Wajeeh et al., 2014)	
	Older	(Jung & Loria, 2010; Nymberg et al., 2019; Rasche et al., 2018)	
	Younger		**Trust does not influence intentions directly.** (Almazroi et al., 2022; Khan et al., 2019)
Privacy Concerns/Risk	General	(Angst & Agarwal, 2009; Wei et al., 2020)	
	Older	(Dontje et al., 2014; Pywell et al., 2020; Vance Wilson & Lankton, 2004)	
	Younger	**Privacy Concerns is positively related to intentions.** (Almazroi et al., 2022)	
E-health Literacy	General	(Alsahafi et al., 2022; Uslu & İpek, 2022)	
	Older	(Nymberg et al., 2019; Pywell et al., 2020)	
	Younger	**E-health literacy is positively related to intentions.**	

First, no significant relationship has been detected between effort expectancy, one of the fundamental constructs of technology adoption, incorporated from TAM to UTAUT, and intentions. Interestingly, studies on e-health system adoption have predominantly confirmed this relationship in various health and mHealth settings. However, there are exceptions where no significant relationship was observed. This includes Lee et al. (2020), who worked on a general population sample in Taiwan and Almazroi et al. (2022), whose study was on a younger sample (88%<25 years old) in Saudi Arabia. Findings from related studies also indicate a relatively weak influence of effort expectancy on intentions (Arfi et al., 2021). Few studies on health professionals even suggested that UTAUT may not be adequate for health systems adoption in settings such as developing countries (Bawack & Kala Kamdjoug, 2018). Evidence from similar contexts such as young generations' adoption of e-Government services demonstrated that effort expectancy is an insignificant barrier to adoption (Lallmahomed et al., 2017; Mensah, 2019; Verkijika & De Wet, 2018). It is apparent that context is critical and that UTAUT, a popular technology acceptance model, is not valid in its entirety in the current PAEHR setting.

This may be primarily attributed to the characteristics of the Gen-Z sample, the members of which have good digital literacy and can use PAEHR systems without significant issues. It should also be noted that only 12% of nonuser respondents indicated that they perceive the PAEHR system to be complicated. This signifies that ease of use, one of the main barriers considered in the literature to e-health system use, is inconsequential for Gen-Z member students. A relevant policy implication is that efforts and resources may be shifted from improving ease of use to elsewhere in order to increase the adoption of younger generations.

Among the significant factors that influence intentions, social influence had the strongest effect, which supports the findings of studies on the general population (Arfi et al., 2021; El-Wajeeh et al., 2014; Kijsanayotin et al., 2009; Zhao et al., 2018) and also on older generational cohorts (e.g. Cimperman et al., 2016). Similar findings were observed in studies on medical staff where social influence had a strong effect on e-health adoption as well (Arfi et al., 2021). Surprisingly literature on e-health adoption by younger populations has arrived at conflicting conclusions as several of them failed to detect this proposed relationship (Suwannapusit, 2021; Tavares & Oliveira, 2016; Yuan et al., 2015), while others did (Keen & Roberts 2017). Moreover, there is evidence of the significance of age in moderating the social influence-intentions relationship in the e-health context (Arfi et al., 2021). Age was also observed to influence attitudes, use frequency and perceptions in health systems adoption in several settings (Bawack & Kala Kamdjoug, 2018; Farhan et al., 2021; Tulu et al., 2016). This emerges as an important theoretical implication as further studies on younger generations are needed in the e-health context to enable further comparisons. Moreover, studies with large samples that enable generational comparisons and multigroup analysis will shed light on the reasons for such conflicting findings.

From a practitioner and policy maker perspective, social influence emerged as a noteworthy factor that can be used to promote health systems to Gen-Z. This digitally native generation has mostly incorporated social media into their daily lives and gets influenced by social groups and peers considerably, with these influences affecting their digital health product and service use (Cheung et al., 2020). Health system promotion campaigns should focus on the use of influencers and peer groups to promote e-health systems to Gen-Z, on whom social influence has a stronger impact than on older generations.

Performance expectancy had the second strongest influence on intentions, implying that when respondents perceive PAEHR to be useful, they develop positive intentions to continue using it. This finding also parallels previous studies such as Albar & Hoque (2019), Alloghani et al., (2015), Tavares and Oliviera (2016) and Yuan et al. (2015). Essentially, the respondents perceived the PAEHR as useful (performance expectancy mean: 5.7 over 7), and these perceptions significantly influenced behavioural intentions. Moreover, 18% of the non-users mentioned lack of usefulness and benefits as a significant factor that affected their decision to not use the PAEHR. It is apparent that performance expectancy is influential in initial use as well as continued usage decisions. Despite their relatively good health compared to older generational cohorts, Gen-Z users perceived the PAEHR system as useful and planned to continue using it.

Basic features (e.g. access to personal prescriptions, laboratory, radiology results, booking appointments, etc.), as well as value-added services such as navigation via maps and requests for emergency ambulance service on mobile devices, provide adequate value to Gen-Z members. Nevertheless, other services can be incorporated into e-pulse to make it even more functional. An immediate policy implication to offer further value to users and one which may influence higher usage, is the inclusion of features such as registering for organ transplantation, shared decision-making on health policy, teleconsultations, chat and messaging services. (Tulu et al., 2016; WHO, 2016). Moreover, policy makers should also consider providing features that are of higher significance for Gen-Z, such as sexual health, sports or activity tracking, and eating habits (Yuan et al., 2015).

In addition, the relationship between performance expectancy and intentions emerged to be significantly higher for the high-experience subsample compared to the low-experience subsample. This indicates that functionality and benefits offered by the system will have a stronger influence on users' usage intentions if their interaction with the system can be increased. Health system sponsors should focus on providing ways to increase the use frequency of PAEHRs. Certain exclusive benefits unique to PAEHRs can help in increasing trial and frequency of use that will, in turn, result in higher adoption.

E-health literacy was also observed to be instrumental in strengthening intentions to continue using PAEHRs. There is a lack of literature testing for this relationship on younger samples, yet this is a finding that has been validated in relevant studies on other cohorts such as the general population and older demographics (Alsahafi et al., 2022; Nymberg et al., 2019; Pywell et al., 2020; Uslu & İpek, 2022). In this study, it became evident that individuals who perceive themselves to be more proficient in finding, accessing, evaluating, and using digital health information effectively are more inclined to adopt PAEHRs. Despite their inherent digital skills, several Gen-Z nonusers (10%) have indicated that they don't have adequate information on the system, or on how to access and use the system. This is a barrier that is partly attributable to e-health literacy. Policy makers' efforts to improve general health literacy should also be complemented by a focus on establishing relevant digital skills to improve such health system usage. E-health training can be integrated into education curricula to establish literacy among younger generations, which in turn will contribute to public health (Liu & Xiao, 2021).

The proposed effect of facilitating conditions on intentions emerged to be insignificant, supporting the findings of several studies on younger populations (Keen & Roberts, 2017; Suwannapusit, 2021; Tavares & Oliveira, 2016; Yuan et al., 2015). Conflicting findings observed in the literature also suggest differences in perceptions and intentions between generations. For instance, studies on general and older samples consistently reported the influence of facilitating conditions on intentions to use e-health systems (Arfi et al., 2021; Cajita et al., 2018; Lee et al., 2020; Zibrik et al., 2015). However, studies investigating EHR and m-health adoption of college students failed to detect a significant relationship between facilitating conditions and intentions (Keen & Roberts, 2017; Suwannapusit, 2021; Tavares & Oliveira, 2016; Yuan et al., 2015). Therefore, the validity of the UTAUT model in younger generations' health system adoption in its entirety is up for debate. The free-to-use PAEHR system and the mobile application, in addition to the high digital proficiency of the Gen-Z sample, apparently weakened the significance of this relationship. In similar studies, free-to-use systems and mobile apps and relatively high literacy of students and younger generations may have led to similar conclusions (Keen & Roberts, 2017). This highlights that facilitating conditions are less likely to emerge as a key obstacle among the educated and younger generations such as the current sample. Efforts may therefore primarily be allocated elsewhere to improve the adoption of e-health systems such as PAEHRs.

The results also revealed that privacy concerns are negatively related to behavioural intentions. This finding confirms the extant literature (Almazroi et al., 2022; Angst & Agarwal, 2009; Dontje et al., 2014; Pywell et al., 2020; Wilson et al., 2021) and indicates that young individuals' concerns about unauthorized access and unintended use of their health information are significant deterrents to PAEHR adoption. This is a well-established relationship observed in numerous studies on a variety of populations, as highlighted in Table 8. Reluctance to provide personal health information could impede the success of state-sponsored health systems and preventive medicine programs such as PAEHR. Not surprisingly, this factor was mentioned by 16% of nonusers as the main reason for not using the system. Despite comprehensive legislation on personal data protection in Turkey which came to force in 2016, privacy concerns are still a valid issue. Thus, privacy concerns should be addressed by health policy makers with further health-specific legislation, also by providing transparency and user control over the information stored and shared (Dontje et al., 2014; Patel et al., 2012). Transparency is considered a significant factor that influences Gen-Z's behavioural intentions in various settings and Gen-Z members are believed to be detail-oriented (e.g. Chillakuri, 2020). Given that there is only one general setting that allows users to disable access to all personal health information stored on e-pulse, more detailed controls can be added to the system to enable customized control.

Moreover, providing users with a convenient way to understand who accessed their personal health information, a feature similar to Denmark's system (Bonomi, 2016), can be incorporated into e-Pulse to increase transparency. These extra features will improve transparency and the control over personal health data and thus will help in decreasing the privacy concerns of Gen-Z members.

Finally, the results failed to confirm that trust is positively related to intentions, contradicting the findings of studies on general and older samples (Alloghani et al., 2015; El-Wajeeh et al., 2014; Jung & Loria, 2010; Nymberg et al., 2019; Rasche et al., 2018). On the other hand, this finding is in accordance with other ehealth adoption studies on younger populations. Almazroi (2022) failed to find any significant influence of trust on intentions on a Gen-Z sample; similarly, Khan et al. (2019) found an insignificant influence of trust on intention to use e-health systems in their study on a younger sample (%85 <34 years). These findings point out that trust is not deemed a significant barrier to e-health system adoption for younger generations.

Our findings, on the other hand, highlighted trust's role in offsetting respondents' privacy concerns. Identifying the trust and risk relationship in an electronic healthcare system context can be counted among the theoretical contributions of this study. Improving trust in health institutions will not directly affect behavioural intentions among Gen-Z members. However, establishing such trust among the younger populace at an early age will be influential in overcoming the privacy risk barrier, which is considered a major obstacle to the wider adoption of PAEHRs (Honein-Abouhaidar et al., 2020; Jung & Loria, 2010). This will have an indirect impact on the behavioural intentions of Gen-Z and can motivate them to continue adopting e-health systems.

Limitations

Given the study design chosen, this study's findings are limited in several ways. First, the perceptions were measured via a self-reported instrument, a questionnaire. In addition, the sample was chosen using purposive sampling, a non-random sampling method among university students. Thus, one future research avenue is utilizing a larger sample that reflects the target population in a better way. This may also provide the opportunity to carry out multi-group analyses to reveal possible differences among generations that can shed light on differing user perceptions and behavioral intentions with regards to e-health system adoption. Another future research direction is to design a longitudinal study and apply a similar model repeatedly at multiple intervals in time to observe the actual usage behaviour of participants. This may lead to deeper insights into the adoption and continued usage behaviour itself and provide further insights into system features. Moreover, future research founded upon experimental methods will be of value to complement the findings of this study. Given that experimental studies generally provide more accurate results on the proposed relationships between the variables, the weak relationships observed in the present study and the conflicting findings in the literature may be pondered in more detail via such studies.

Conclusion

Empowered by information and communication technologies, individuals have begun to assume a more active role in their health care decisions in the last few decades. While electronic health records support the effectiveness and efficiency of the health system in the provision of health services, they have been indispensable for access to health services during the pandemic period. The results of this study provide valuable information to health policy makers, who aim for more effective and efficient health systems in post-pandemic service delivery in order to develop strategies for reaching young people.

Against this backdrop, the present study contributes to the current knowledge on electronic health records in several ways. First, the context of the study differs from the norm and focuses on Turkey, an influential emerging economy. Turkey has achieved remarkable improvements in several aspects of the health system following the implementation of a Health Transformation Program in 2003, as accessibility, quality and efficiency of health care services have improved (Tatar et al., 2011). Second, Gen-Z, an influential generation who have been mostly overlooked in health systems research, was chosen as the focal population of the study. Given their digital skills and their influence on both peers and older family members, they are expected to be instrumental in improving public health. Third, according to the results, traditional technology adoption theories are valid only to a certain extent in the current health systems (PAEHR) adoption setting. The current findings enrich the extant literature by adding trust, privacy concerns and e-health literacy constructs to UTAUT and highlighting the importance of user privacy concerns and e-health literacy. The privacy risk barrier appears to be a significant determinant of young people's intentions to use PAEHRs, which should be addressed by healthcare policy-makers to boost younger people's adoption of PAEHRs. The significant role of a major factor in technology adoption, effort expectancy, was not confirmed in this study. This phenomenon, when considered along with the insignificant effect of facilitating conditions hints at how generational differences can affect e-health system use. It became evident that efforts in improving the ease of use of EHRs may not have any noteworthy influence on younger generations' adoption of such health systems. This finding can be categorized as a key highlight of Gen-Z characteristics in developing countries. Surprisingly, social influence emerged to have the greatest impact on adoption among all factors tested, something which conflicts with the findings of similar studies on younger generations. The important role of peers and social groups in shaping the attitudes and intentions of the younger populace became evident in this study. As a result, efforts to benefit from such social influence in increasing Gen-Z's EHR adoption instead of focusing on ease of use will be more appropriate. Further empirical studies on younger generational cohorts and large samples that enable multi-group analysis will help in supporting or refuting the present study's findings and health system policy implications.

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APPENDIX A: Scales

Code	Item	Source
EHL1	I know how to find helpful health resources on the Internet	(Norman & Skinner, 2006)
EHL2	I know how to use the Internet to answer my health questions	
EHL3	I know what health resources are available on the Internet	
EHL4	I know where to find helpful health resources on the Internet	
EHL5	I know how to use the health information I find on the Internet to help me	
EHL6	I have the skills I need to evaluate the health resources I find on the Internet	
EHL7	I can tell high quality from low quality health resources on the Internet	
EHL8	I feel confident in using information from the Internet to make health decisions	
TRU1	There would be reliable third party available (through Govt health authorities or other providers) to assure the security of the EHR system.	(Andrews et al., 2014)
TRU2	I would trust the Government to provide ways to protect my personal information in the EHR system.	
TRU3	I believe that healthcare providers involved with EHR would not divulge their personal data to other parties without permission.	
TRU4	I would trust my doctor or other providers who have authorized access to my EHR to properly manage my health information.	
TRU5	Doctors and other authorized health providers could be trusted to protect the information in my EHR.	
PRF1	Using EHR Portals will support critical aspects of my healthcare.	(Tavares & Oliveira, 2016)
PRF2	Using EHR Portals will enhance my effectiveness in managing my healthcare.	
PRF3	Overall, EHR Portals will be useful in managing my healthcare.	
EFE1	Learning how to use EHR Portals is easy for me.	
EFE2	My interaction with EHR Portals is clear and understandable.	
EFE3	I find EHR Portals easy to use.	
EFE4	It is easy for me to become skilful at using EHR.	
SOC1	People who are important to me think that I should use EHR	
SOC2	People who influence my behaviour think that I should use EHR	
SOC3	People whose opinions that I value prefer that I use EHR.	
FAC1	I have the resources necessary to use EHR.	
FAC2	I have the knowledge necessary to use EHR.	
FAC3	EHR Portals is compatible with other technologies I use.	
FAC4	I can get help from others when I have difficulties with using EHR	
INT1	I intend to use EHR.	
INT2	I intend to use EHR in the next months.	
INT3	I plan to use EHR frequently.	
PRI1	I am concerned that the information I submit to EHR system could be misused.	(Bansal et al., 2010; Guo et al., 2016)
PRI2	I am concerned that a person can find private information about me on the EHR system	
PRI3	I am concerned about providing personal information to EHR system because of what others might do with it.	
PRI4	I am concerned about providing personal information to EHR system because it could be used in a way I did not foresee.	
PRI5	It bothers me to give personal information to different health care entities	

EHL: E-health literacy, EFE: Effort expectation, FAC: Facilitating conditions, INT: Continued Usage Intentions, PRI: Privacy concerns, TRU: Trust, SOC: Social influence, PRF: Performance expectancy